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Wireless sensor networks scheduling for full angle coverage

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Abstract Many current studies in tracking and surveillance assume that a target can be monitored by a single sensor. However, there are situations where a sensor can only monitor a certain portion of the object. Examples include image capturing and coastline monitoring. In our previous work, we develop the *Minimum Cost Cover* algorithm to identify a set of sensors which preserve 360° coverage of a target with minimum cost, such that when different cost functions for the sensors are used, covers with different optimization objectives can be identified. In this work, we study the scheduling problem to monitor a target continuously with full angle coverage. To increase network lifetime, we develop several algorithms by adopting different cost functions in selecting the sensors. We evaluate the performance of our schemes through extensive simulations. The simulation results show that our proposed Conditional Scheduling metric can help to improve the network lifetime as well as the time to the first node failure.

Keywords Angle coverage · Minimum cost cover · Scheduling

1 Introduction

Wireless sensor network is a network consisting of 1,000s of sensors spanning over a large geographical area. The sensors are able to communicate with each other, exchange information and perform tasks collaboratively. It has been an emerging technology in habitat monitoring, target tracking, disaster management, etc. (Pottie and Kaiser 2000; Zhao and Guibas

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2004). Usually, a sensor is very small in size and powered by battery which is unlikely to be rechargeable. The limited availability of energy within sensor nodes implies that the time during which all the sensors are able to sense, transmit, receive and process information is limited. Therefore, each sensor should be used carefully in order to prolong the network lifetime.

Coverage problem, which is concerned with how well a target or an area is monitored by the sensors, is a fundamental issue in wireless sensor networks. In the traditional target or area coverage problem, a set of sensors is identified such that each given region or target is covered by at least k sensors in the set (Huang and Tseng 2003). In our previous work (Chow et al. 2007a,b), however, we focus on the angle coverage problem. In Chow et al. (2007a), we studied the *Minimum Cover* problem and developed a distributed algorithm to identify the minimum set of sensors which preserves 360° coverage in visual sensor networks, where the collected data are images. In Chow et al. (2007b), we formally proved that the angle coverage problem can be transformed into a well known problem, *the shortest path problem* (Cormen et al. 2001), which can be solved by Dijkstra's algorithm. To solve the problem in a decentralized manner, we developed the *Minimum Cost Cover* algorithm to identify a set of sensors that preserves the full angle coverage with minimum cost. Furthermore, by assigning different cost functions to the sensors, different optimization objectives can be achieved.

In this work, we study the scheduling problem of the sensors in order to monitor a target continuously with 360° coverage. We consider a tracking system where an object of interest is monitored by the sensors surrounding it. The data of interest can be temperature, humidity, light intensity or images. We adopt our Minimum Cover and Minimum Cost Cover algorithms to develop several coverage-preserving scheduling schemes. Their performances are evaluated through extensive simulations.

The rest of this paper is organized as follows: Sect. 2 presents the related work. Section 3 describes the Network Model. Section 4 summarizes the Minimum Cover and Minimum Cost Cover problems. We then propose five scheduling metrics in Sect. 5. This is followed by Sect. 6 that presents the simulation results and some concluding remarks in Sect. 7.

2 Related work

There has been extensive research on extending the lifetime of sensor networks (Dong 2005; Schurgers and Srivastava 2001). However, other than lifetime, maintaining sufficient coverage is another important concern in sensor networks. Scheduling the sensor nodes activity to alternate between active and sleep mode is one of the important techniques to prolong the network lifetime (Huang et al. 2005). Cardei et al. (1984) study the energy-efficient target coverage problem in wireless sensor networks. They consider a number of targets with known locations that needed to be continuously observed by the sensors. The objective is to have each location in the physical space of target within the sensing range of at least one sensor. An efficient method is proposed to extend the sensor network lifetime by dividing the sensor nodes into a number of sets, such that each set completely covers all the targets, and these sensor sets are scheduled to alternate between active state and sleep state. However, their proposed linear programming and greedy heuristics are centralized, which is not desirable in wireless sensor networks. Alfieri et al. (2004) also attempted to maximize the network lifetime by scheduling the sensors' activity using a greedy algorithm. Each sensor decides independently with a given probability whether to be an active or inactive state initially in the selection process. The active sensors (i.e. the selected sub-set) then check if they can guarantee the required coverage level. If not, this sub-set is discarded and the algorithm restarts. They assume that the energy consumption in checking coverage level and discarding a selected sub-set is negligible. Yet, this assumption may not be appropriate, because message transmission has been shown to be the major source of energy dissipation in sensor networks (Pottie and Kaiser 2000; Raghunathan et al. 2002). Liu et al. (2005) proposed an optimal solution for finding a target watching schedule for sensors in order to achieve the maximal lifetime. However, the proposed solution is also centralized, which is not desirable. Furthermore, it should be noted that the studies mentioned above address the area coverage problem, but not the angle coverage problem that we study in our previous work (Chow et al. 2007a,b,c).

In this paper, we study the scheduling problem where the perimeter of a target has to be continuously monitored. We have shown that the problem of identifying a minimum cost cover can be reduced to the shortest path problem (Chow et al. 2007a). In this respect, the scheduling problem is similar to the Internet *traffic engineering* problem (Awduche 1999) that when we find a path from the source to the destination, apart from finding a minimum cost one, we would also like to find one that utilizes the resource efficiently so that the network can accommodate more future requests. Leveraging on the techniques proposed in traffic engineering and the power-aware routing protocols described in Toh (2001) and Singh et al. (1998), we develop several schemes for prolonging the network lifetime.

3 Network model

We consider a tracking system where an object of interest is monitored by the sensors surrounding it. We assume that the sensors are randomly distributed and each sensor knows its physical location by means of GPS or some localization algorithms (Liang et al. 2006; Patro 2004).

3.1 Cover range

Cover Range is defined as the portion of perimeter of the object of interest covered by a sensor node. In this paper, we represent the cover range in terms of angle for ease of discussion. As long as sensors are able to identify the ranges of the perimeter of the object of interest it can cover, our algorithms work. We now briefly describe how a sensor obtains its cover range if the object of interest is cylindrical with a radius R_o as shown in Fig. 1.

3.1.1 General sensor networks

In general sensor networks, the cover range of a sensor is determined by its sensing range and the distance between the node and the centre of the object of interest. In Fig. 1, β is the covered angle, κ is the sensing range of the sensor and d is the node distance. Since every sensor knows its physical location, d is known. The covered angle can then be calculated by using the following equation:

$$\beta = 2\cos^{-1}\left\{\frac{{R_o}^2 + d^2 - \kappa^2}{2dR_o}\right\}. \tag{1}$$

It is easy to see from Fig. 1 that only the sensors with a node distance less than or equal to $R_o + \kappa$ are able to cover the perimeter of the target. If κ is a constant, the closer the sensor node to the object of interest, the larger the cover range is.

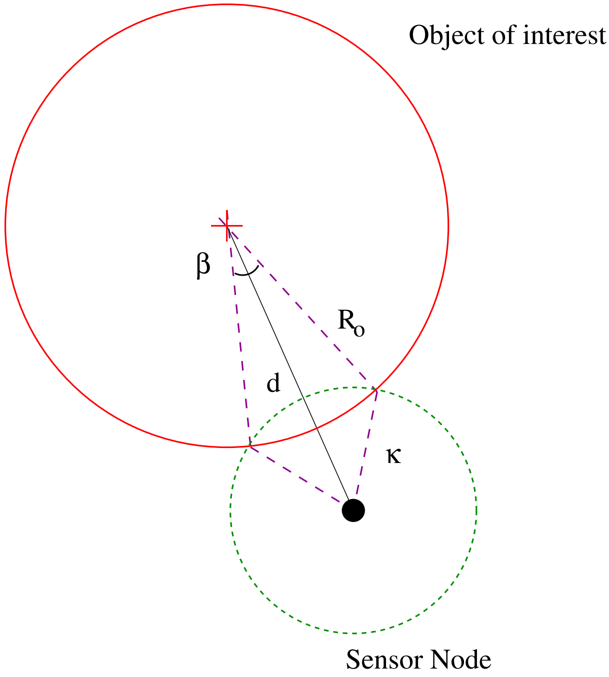

Fig. 1 Relationship between the object of interest and the sensor in a general sensor network

3.1.2 *Visual sensor networks*

Visual Sensor Network (VSN) is a particular type of wireless sensor networks. In VSN, all sensor nodes are equipped with cameras and they are responsible for capturing the images of the target. Visual sensors have the unique feature that the objects covered by the camera can be far away from nodes as they can capture images of objects that are not necessarily in the camera's vicinity. Unlike general sensor networks, the cover range of visual sensors are determined by the cameras' field-of-view (FOV) instead of sensing range. Cover range is equivalent to the angle of view captured by a camera node. The capture range of a camera node with FOV θ is illustrated in Fig. 2. By applying image-based localization algorithms such as Lee and Aghajan (2006) and McCormick et al. (2006), every sensor knows its physical location and camera orientation. Provided we know the physical locations of the node and the object, we can compute their distance R_1, and knowing the orientation of the camera would further allow us to calculate the cover range of the object by simple geometry.

It can be seen from the two scenarios in Fig. 2 that in contrast with the general sensor network, putting the camera closer to the object would in fact reduce the capture range. On the other hand, this would increase the resolution of the images because there are more pixels for the same region to record higher spatial frequencies. Thus, there is a tradeoff between image resolution and node distance.

3.2 Cover

Given a set of sensors S, let the cover range of sensor node $i \in S$ be $V(i) = [s_i, t_i]$. If $t_i < s_i$, sensor i covers 0° of the perimeter. A set $D \subseteq S$ is a *cover* if for each angle $\gamma \in [0°, 360°]$, there exists a sensor i in D such that $\gamma \in [s_i, t_i]$. In other words, $\bigcup_{i \in D} V(i) = [0°, 360°]$.

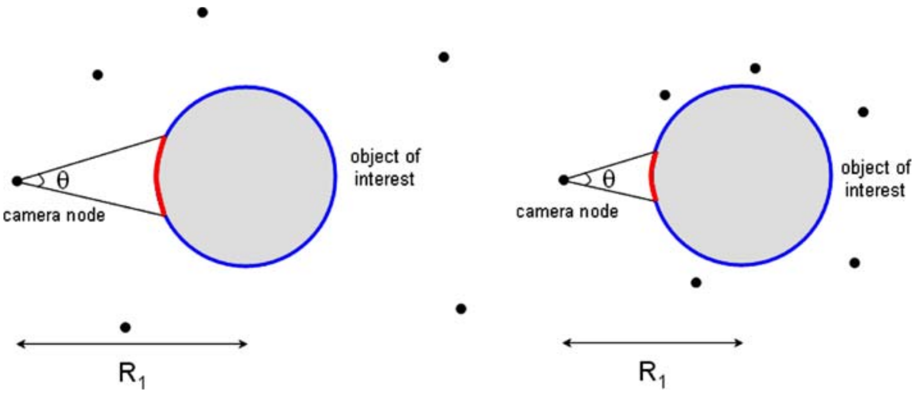

Fig. 2 Relationship between the object of interest and the sensor in a visual sensor network

Fig. 3 Illustrations for various possibilities of sensor covers

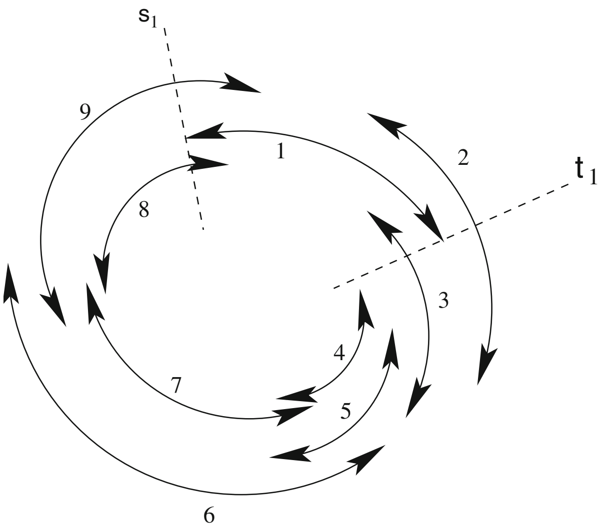

Figure 3 illustrates a scenario of 9 sensors surrounding an object of interest. Each arrow represents the cover range of a node. {1, 3, 5, 7, 8}, {1, 2, 3, 5, 6, 9}, and {1, 3, 5, 7, 9} are all valid covers.

3.3 Network lifetime

In this work, *network lifetime* is defined as the time until the target cannot be monitored with 360° coverage. We adopt the cycle-based scheduling mechanism as in Cardei et al. (2006); Deng et al. (2006). In each cycle, a set of sensors is turned on to monitor the target. Those sensors that are not in the set can go to sleep mode to conserve energy. *Node lifetime* is defined as the time until the node does not have enough energy to monitor the target in the whole cycle period. Our objective is to monitor the object of interest with 360° coverage as long as possible.

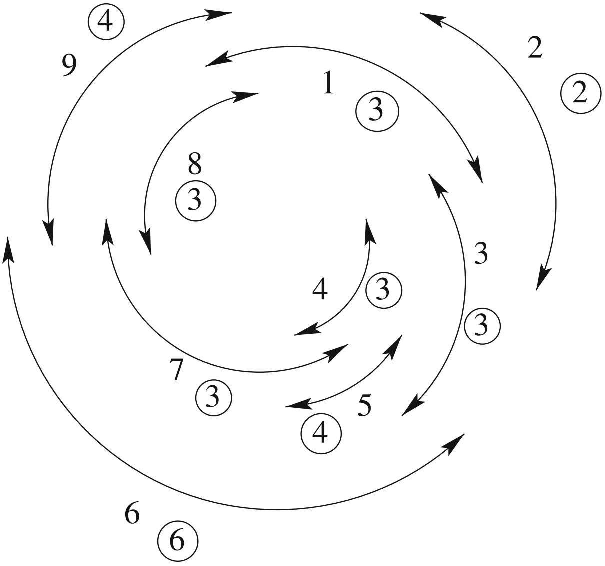

Fig. 4 Illustration of a Minimum Cost Cover

4 Minimum cover and minimum cost cover

Intuitively, we should use as little energy as possible in each cycle in order to prolong the lifetime. In this section, we summarize our earlier work in identifying a set of sensors that fulfills the minimum cost criterion. This also serves as the basis upon which we develop the scheduling schemes in Sect. 5.

4.1 Definitions

Minimum Cover is a set of sensors with the smallest size which preserves the entire cover range. Referring to the example in Fig. 4, both $\{1, 3, 6, 9\}$, $\{1, 2, 3, 5, 6, 9\}$ and $\{1, 3, 5, 7, 9\}$ are covers while $\{1, 3, 6, 9\}$ is also a minimum cover. Minimum cover is not necessarily unique.

Minimum Cost Cover is a cover that has minimum cost among all covers. For example, in Fig. 4, the number in circle represents the cost of each node. $\{1, 2, 4, 7, 8\}$ is the Minimum Cost Cover.

4.2 Finding a minimum cover

In our previous work (Chow et al. 2007a), we developed an optimal solution to identify a minimum cover that preserves all the covered range in a distributed manner, where each sensor needs to obtain the cover ranges of their neighbors only. That is, if the cover range of sensor i is $[s_i, t_i]$, i knows the cover range of neighbor j if $s_i \leq s_j \leq t_i$ or $s_i \leq t_j \leq t_i$. Referring to the example in Fig. 3, Sensor 1 knows the cover ranges of neighbors 2, 3, 8 and 9. Sensor node k must be in a minimum cover if it includes an angle that is not covered by others. We refer to such a node as a *default member*.

Due to space limitation, we refer interested readers for the detailed discussion of the algorithm in Chow et al. (2007a). In this paper, we use the example in Fig. 3 to illustrate the idea. After obtaining neighborhood information, each node checks whether it is a default member. In this example, Node 1 is a default member. Then, it informs its neighbors, Nodes 2, 3, 8, and 9, that it is selected, and then identifies the next sensor to be included in the minimum cover. Intuitively, Node 1 should find a node whose covered range overlaps with its own and goes as far as possible. The searching procedure can be done either clockwise or anticlockwise, but not both. Suppose the clockwise direction is adopted in this example, then Node 1 selects Node 3 and Node 1 sends a message to the latter informing that it is selected. Node 3 then finds the next sensor, Node 5, which in turn selects Node 6. Similarly, it selects Node 9. When the latter knows that it is selected and realizes that it has a neighbor (Node 1) that has been already selected, it stops the search. At this stage, a minimum cover $\{1, 3, 5, 6, 9\}$ is identified. Although no sensor knows the whole minimum cover, each of them knows whether it is in the cover or not and can send its data accordingly.

When a default member exists, only those sensors that are selected to be in the minimum cover would send out a message. Therefore, the message overhead is very small. It is also worth noting that the mechanism works if there are more than one default members. All of them will start searching for the next sensor. Once a selected node detects that it has a selected neighbor, it stops the search. It is also possible that there is no default member. In this case, those sensors which cover 0° can invoke the process, after not hearing anything for some time. Each of these nodes would identify its own "minimum cover" and they can find out which one is the real minimum cover after exchanging the cover information. Nevertheless, the message overhead is increased. We can reduce the overhead by allowing only one sensor to invoke the process but the cover found may not be optimal.

4.3 Finding a minimum cost cover

We now describe the algorithm for finding a minimum cost cover when each sensor i is associated with a cost $f(i)$. The cost of a cover D, $f(D)$, is the total cost of the sensors in the cover, that is, $f(D) = \sum_{i \in D} f(i)$. A minimum cost cover is a cover that has the minimum cost among all covers. Formally, M is a minimum cost cover if $f(M) \leq f(D)$ for every cover $D \subseteq S$. By setting $f(i) = 1$ for all i, the minimum cost cover problem can be reduced to the minimum cover problem.

In Chow et al. (2007b), we formally proved that the minimum cost cover problem can be reduced the shortest path problem. With a sensor set C, we construct a directed graph $G_C = (V, E)$ such that $V = C \cup \{S, T\}$ where S and T are the source and destination of our minimum cost path problem, respectively. Each edge in E is associated with a non-negative cost. Let $w(i, j)$ denote the cost of edge $(i, j) \in E$. There are three types of edges:

(1) Edges starting from S:
$(S, i) \in E$ if $i \in C$ and $s_i = 0°$; $w(S, i) = f(i)$
(2) Edges going to T:
$(i, T) \in E$ if $i \in C$ and $t_i = 360°$; $w(i, T) = 0$
(3) Edges linking nodes in C:
$(i, j) \in E$ if $s_i < s_j \leq t_i$ and $t_i < t_j$; $w(i, j) = f(j)$

An example is given in Fig. 5. The cost of an edge is the cost of the sensor node it is directed to. By defining E this way, a path from S to T first traverses a node i with starting view angle 0°, then goes to another node with overlapping angle of view with i, and continues until the path ends at a node with ending angle as 360°. The set of the nodes in the path is a cover.

Shortest path problem is a well-studied problem and the distance vector protocol is a distributed solution. Due to the acyclic nature of our graph construction, a more efficient

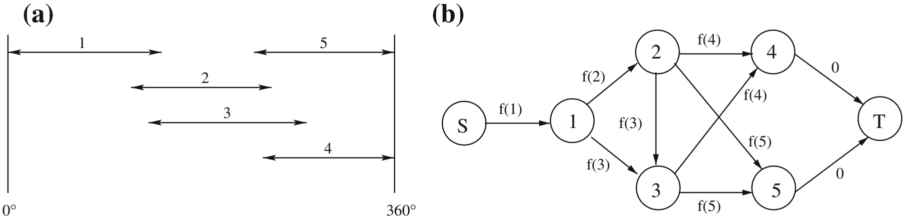

Fig. 5 Illustration of the transformation from a cover example to a graph. (**a**) Cover example. (**b**) Graph constructed

protocol can be developed. The message overhead of our optimal solution when there is at least one default member is $O(N)$ where N is the number of sensors. Similar to the situation in finding a minimum cover, if there is no default member, there is a tradeoff between message overhead and optimality.

5 Scheduling schemes

The central question in this work is to schedule sensors to monitor the target continuously with 360° coverage. In this section, we present five different scheduling schemes which extend our work on the Minimum Cover or Minimum Cost Cover algorithms.

5.1 Minimum battery cost cover (MBC)

Minimum Cover can reduce the number of sensors involved in each monitoring cycle and thus reduce the total energy consumption in sensing. However, it has a critical disadvantage that it cannot prevent nodes from being overused. Minimum Cover has a tendency to select the same set of sensors, causing the battery of those nodes to exhaust quickly. Toh (2001) and Singh et al. (1998) suggest that the remaining battery capacity of each node is a more accurate metric to describe the lifetime. They study the Minimum Battery Cost Routing (MBCR) and show that the remaining battery capacity can be incorporated directly into the routing protocol. We adopt this idea into the Minimum Cost Cover problem. Let π_i be the remaining battery capacity of node i. We define $f(i)$ as the battery cost function of node i, i.e.

$$f(i) = \frac{1}{\pi_i}. \tag{2}$$

As the remaining battery capacity decreases, the value of $f(i)$ increases, making it a "dynamic cost" that increases with time. This metric forces the choice of a node with more remaining battery capacity. Unlike Minimum Cover, no specific set of sensors will be chosen all the time, which helps to prevent nodes from being overused.

Referring to the example in Fig. 6, nodes 1–13 are the sensors which are able to monitor the object of interest. Suppose there are three possible covers $\{1, 4, 7, 10, 12\}(C_1)$, $\{2, 5, 8, 11\}$ (C_2) and $\{3, 6, 9, 13\}$ (C_3). The numbers surrounding the sensors indicating the residual battery capacity of the nodes. In this example, C_1 is the MBC. However, after this round, the selected nodes will used up some battery capacity. In the next instance, the MBC is not necessarily be C_1 again.

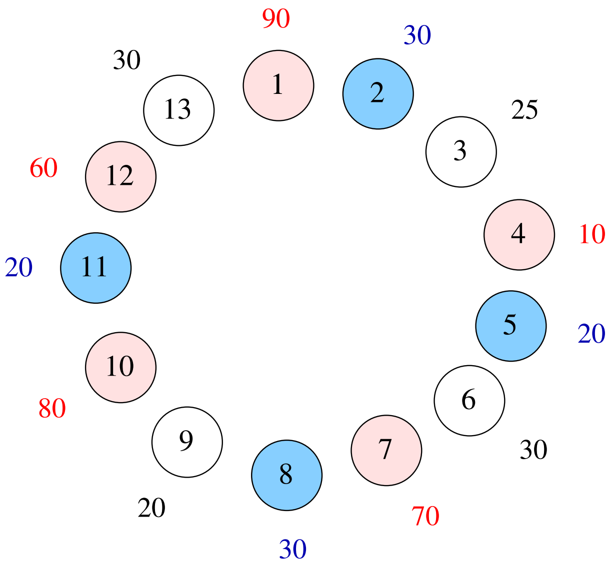

Fig. 6 Minimum Battery Cost Cover example

5.2 Maximum–minimum residual battery capacity cover (Max–Min)

Although MBC can help to prevent nodes from being overused, because only the summation of battery costs is considered, a cover containing nodes with very little residual battery capacity may still be selected. In the previous example, C_1 is selected. If 10 units of battery capacity will be consumed in each cycle of monitoring, node 4 will be depleted, which is undesirable. To solve this problem, we develop the Maximum–Minimum Residual Battery Capacity Cover algorithm.

Maximum–Minimum Residual Energy is a common scheduling metric to prolong the network lifetime. Let the energy cost B_J for cover J be defined as

$$B_J = \min\{\pi_i \mid i \in J\} \tag{3}$$

We aim at finding a cover C with the largest minimum residual energy, i.e.

$$B_C \geq B_J \tag{4}$$

for all valid covers J.

This metric avoids selection of a cover with nodes having the least amount of residual battery capacity among all possible covers. This Max-Min problem can be transformed to the Maximum Bottleneck Problem. Whereas the Minimum Cost Cover problem can be tackled by Dijkstra's algorithm, this problem can be solved by using a modified Dijkstra's algorithm (Malpani and Chen 2002) where $f(i)$, the residual battery capacity, is

$$f(i) = \pi_i. \tag{5}$$

In Fig. 6, the minimum residual battery capacities of C_1, C_2 and C_3 are 10, 20 and 20 respectively. Therefore, the Maximum–Minimum Battery Capacity Cover can be either C_2 or C_3.

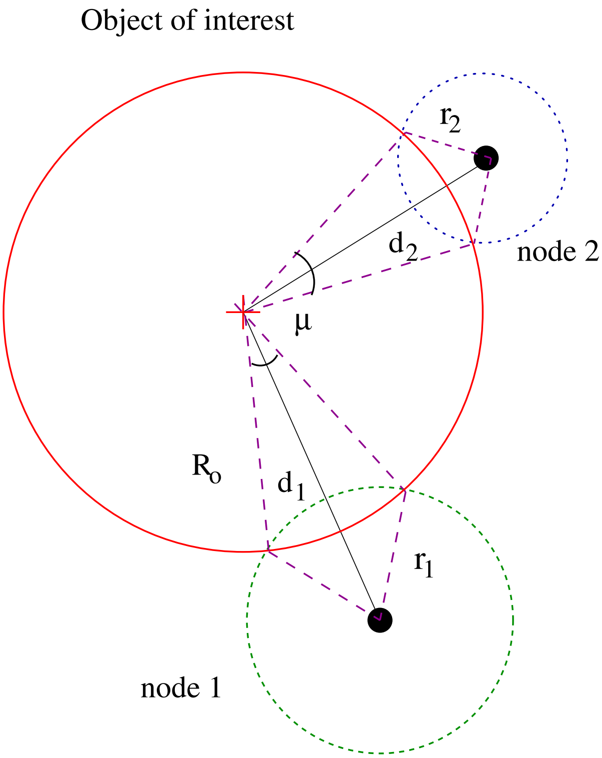

Fig. 7 Illustration of a variable sensing range

5.3 Minimum sensing range cover (MSR)

An important issue in sensor networks is power scarcity, where mechanisms that optimize sensor energy utilization have a great influence on prolonging network lifetime. One common power saving technique is to adjust the sensing range of sensor nodes. Let r_i be the sensing range of node i, the energy e_i consumed in sensing the object is proportional to ${r_i}^2$ Cardei et al. (2006), i.e.

$$e_i \propto {r_i}^2. \tag{6}$$

Referring to Fig. 1, the minimum sensing range of the sensor node would be $d - R_o$. While, it would be advantageous to reduce the sensing ranges to be small from the energy point of view, when it decreases, the cover range of a node decreases and thus more sensors are required to preserve 360° coverage. In this work, we assume that the sensing range of each node is fixed such that all the nodes cover the same amount of the target's perimeter, as illustrated in Fig. 7. Let μ be the desired covered range, the sensing range of node i is set as follows:

$$r_i = \sqrt{{R_o}^2 + {d_i}^2 - 2R_o d_i \cos\frac{\mu}{2}} \tag{7}$$

Figure 7 shows that when the node is closer to the object of interest, its sensing range can be smaller to achieve the same covered range. In this example, $r_2 < r_1$.

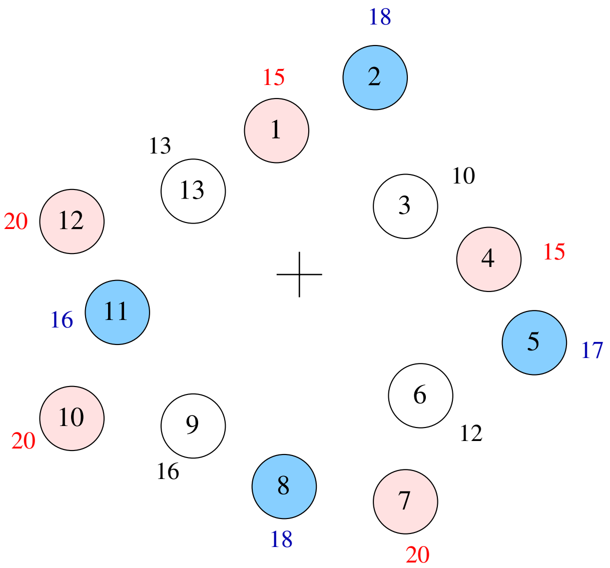

Fig. 8 Minimum Sensing Range Cover example

The MSR metric aims at identifying a cover with the minimum energy consumption in sensing, and this can be achieved by applying the Minimum Cost Cover algorithm. We define $f(i)$ as the sensing range of node i, i.e.

$$f(i) = {r_i}^2 \tag{8}$$

This metric identifies the cover with the smallest sum of sensing ranges, minimizing the energy consumption in sensing. However, while this metric can reduce the total energy consumption in sensing, it cannot prevent nodes from being overused.

In Fig. 8, the "+" represents the centre of the object of interest and the numbers surrounding the nodes represent the sensing ranges. Similar to the previous example, $\{1, 4, 7, 10, 12\}$ (C_1), $\{2, 5, 8, 11\}$ (C_2) and $\{3, 6, 9, 13\}(C_3)$ are the three possible covers. In this case, C_3 is the MSR.

5.4 Hybrid scheduling (Hybrid)

Both MSR and Minimum Cover cannot prevent nodes from overuse because they always select the same set of nodes until a node runs out of energy. MBC and Max–Min approaches can solve this problem but the size of the selected cover is often much larger than that of MSR and Minimum Cover, which may reduce the lifetime of all nodes. Prolonging the network lifetime and using the battery fairly are two conflicting goals which cannot be achieved simultaneously by applying Minimum Cover, MBC or Max–Min alone. Toh (2001) and Singh et al. (1998) also note that applying shortest path or any power-aware routing schemes alone cannot resolve the conflicting goals. Intuitively, when the network is newly formed, all the nodes have adequate battery capacity and the shortest-path routing can be applied. After some time, when the energy resources have fallen below a certain value, nodes should begin using one of the energy-related metrics. We use this idea to develop the *Hybrid Scheduling*.

Let S be the set of sensors that are able to cover the perimeter of the object of interest and γ be the threshold. If $\pi_i \geq \gamma$ $\forall i \in S$, Minimum Cover is applied. Otherwise, Max–Min approach is used. The combination of metrics is not limited to Minimum Cover/Max–Min, it can be Minimum Cover/MBC or any other possible combinations. When a node notices its battery capacity falls below the threshold value, a message will pass around to indicate the switch of scheduling scheme.

5.5 Conditional scheduling

Unlike Hybrid, Conditional Scheduling applies one metric only, which can be any possible scheduling metrics. In Conditional Scheduling, not all the nodes which are able to monitor the target will be considered. Similar to Hybrid, a threshold (γ) is set in Conditional Scheduling, yet the value of γ can change in every round. Suppose S is the set of sensors that are able to monitor the target. In each round of sensing, only the nodes with residual energy π_i greater than or equal to threshold will be involved in the selection process. Let D be the candidate set of each round,

$$D = \{i \mid \pi_i \geq \sigma,\ \forall i \in S\}. \tag{9}$$

The energy consumption in overhead transmission is not negligible when compared with that of sensing. We mentioned before that the message overhead of finding a minimum cost cover is proportional to the number of sensors. Since not all the nodes will be involved in every round of cover selection process, this helps to reduce energy consumption in message communication and thus can prolong the nodes' lifetime.

The performance of Conditional Scheduling depends on the value of γ. We suggest that it can be chosen to be a function of the energy consumption in each round such as sensing and overhead transmission.

5.5.1 Conditional minimum sensing range cover (C_MSR) example

Referring to the example in Fig. 6 without the battery costs. There are three possible covers {1, 4, 7, 10, 12}(C_1), {2, 5, 8, 11} (C_2) and {3, 6, 9, 13} (C_3). For simplicity, we assume that the sum of energy consumption in sensing of the three covers are the same. Let the initial battery capacity be 200, energy needed in sensing be 5 and the energy needed in overhead communication be 10. In the first round of sensing, γ is set to be 200. Therefore, all the nodes are the candidates in the MSR selection process. Suppose C_2 is selected. The residual battery capacity becomes:

$$\pi_i = \begin{cases} 200 - 10 - 5 = 185 & \text{if } i \in C_2 \\ 200 - 10 = 190 & \text{if } i \in C_1 \text{ or } C_3 \end{cases} \tag{10}$$

In the next round, in order to use the nodes more fairly, we should avoid choosing C_2 again. Therefore, γ can be set as 190 and only the nodes in C_1 and C_3 will be considered. Suppose C_3 is then selected, the residual battery capacity of the nodes will become:

$$\pi_i = \begin{cases} 190 - 10 = 180 & \text{if } i \in C_1 \\ 185 & \text{if } i \in C_2 \\ 190 - 10 - 5 = 175 & \text{if } i \in C_3 \end{cases} \tag{11}$$

In the third round, γ is set to be 185 and thus C_2 will be selected. The process continues in the same fashion. In each iteration, γ is decremented by 5. If a cover cannot be found, γ is further decreased by 10 (which is the energy used in finding a cover) until a cover can be found.

6 Simulation

In this section, we present simulation results of our algorithms. They are generated using *J-Sim* (formerly known as JavaSim) (Sobeih et al. 2005). The network area is set to be $(200M \times 200M)$ with 400 grids where M denotes a unit length. The communication range is set to be $25\sqrt{2} = 35.355$ units. We assume that the object of interest is cylindrical with radius of 50 units. We evaluate the performance of the proposed scheduling metrics in a densely populated network where there is exactly one sensor node in each grid. We study two different scenarios: fixed sensing range and variable sensing range.

To facilitate our discussion, we adopt the following notations:

E_m : Energy needed in transmitting or receiving one control message
E_c : Energy needed in sensing per second (for fixed sensing range)
E_r : Energy needed in sensing per second per M^2 (for variable sensing range)

In a densely populated network, it is common that there is no default member and the sensors which cover 0° will invoke the process. In order to find the optimal minimum cover or minimum cost cover, we allow all of the sensors which cover 0° to start the selection process. In order to reduce the message overhead, we may restrict only one of them to invoke the process, though the selected cover may not be optimal. If there are four default members, the message overhead of the optimal case will be four times that of the non-optimal case. In our simulations, we compare the results of the scheduling schemes in optimal and non-optimal cases.

6.1 Fixed sensing range

We assume that all the sensors have identical sensing ranges and the sensing range is set to be 18 units. All the nodes consume the same amount of energy in sensing. Depending on applications, the ratio of power consumption in transmission and sensing can vary substantially. For simplicity, we assume that the sensing duration of each round is 1 s and the initial battery capacity of all the nodes are set to be 200.

In Figs. 9–12, five scheduling schemes are compared when E_c varies:

(1) Minimum Cover (Min Cover)
(2) Conditional Minimum Cover (C_Min)
(3) Hybrid Scheduling, Min Cover/Max–Min, $\gamma = 100$ (Hybrid)
(4) Minimum Battery Cost Cover (MBC)
(5) Maximum–Minimum Residual Energy Cover (Max–Min)

It should be noted that MSR is not compared in the fixed sensing range scenario. This is because when all the nodes possess identical sensing range, the selected cover of MSR is equivalent to minimum cover. Since the message overhead of MSR is much more than that of Min Cover, Min Cover must has a longer network lifetime than MSR.

Figure 9 shows that Min Cover and C_Min have longer network lifetimes than the others. Although MBC, Max–Min and Hybrid can help to prevent nodes from being overused, they often find a larger cover which actually reduces the network lifetime. As mentioned in Sects. 4.2 and 4.3, the only message passing around in Min Cover would be for selected sensors to be included in the minimum cover while the message overhead in Minimum Cost Cover is $O(N)$ if there are N candidates. Therefore, MBC, Max–Min and Hybrid consume much more energy in message communication than Min Cover and C_Min. The simulation results also show that Hybrid has a longer network lifetime than applying Max–Min alone.

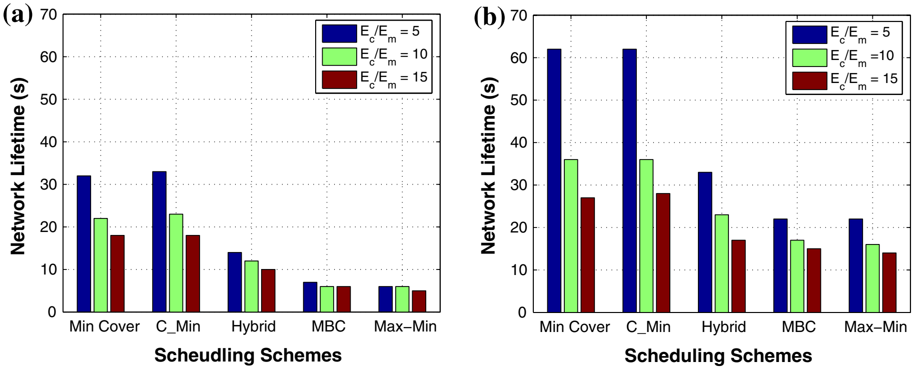

Fig. 9 Network lifetime Comparison when E_c varies (fixed sensing range). (**a**) Optimal.(**b**) Non-Optimal

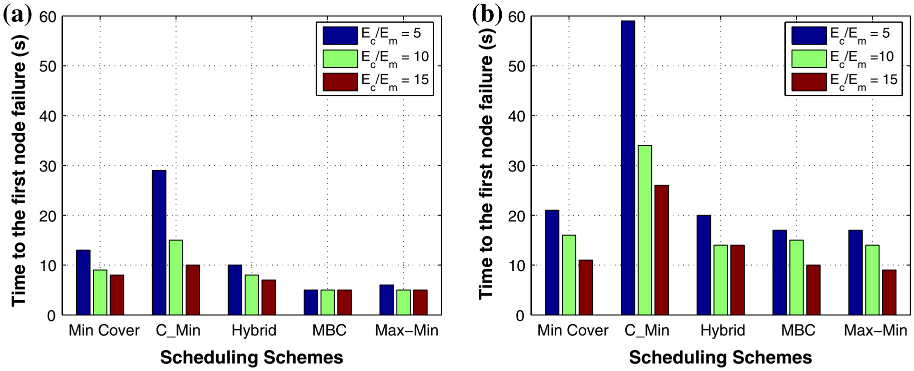

Fig. 10 First node failure comparison when E_c varies (fixed sensing range). (**a**) Optimal. (**b**) Non-Optimal

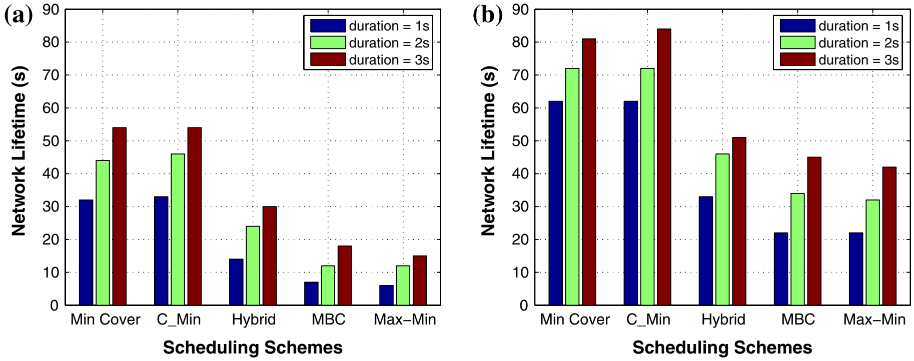

Fig. 11 Network lifetime comparison when sensing duration varies (fixed sensing range). (**a**) Optimal. (**b**) Non-Optimal

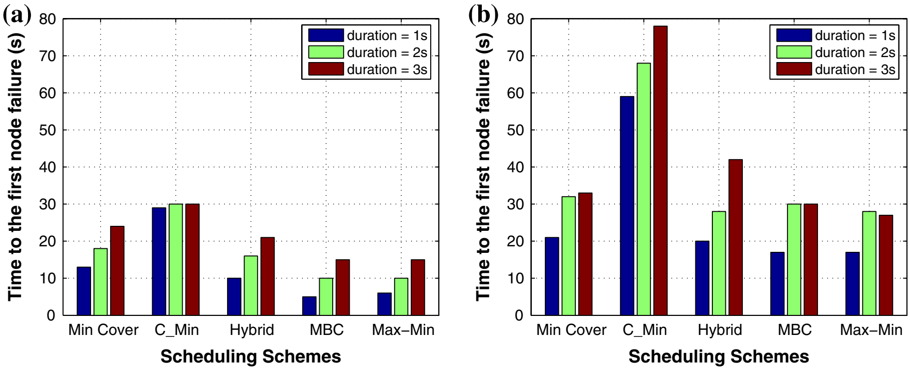

Fig. 12 First node failure comparison when sensing duration varies (fixed sensing range). (**a**) Optimal. (**b**) Non-Optimal

Furthermore, it can be observed that the non-optimal scheduling schemes help to improve the network lifetime. Although the selected covers of non-optimal schemes may be larger than that of optimal schemes, the reduction in message overhead outweighs the increase in the total energy consumption in sensing.

Figure 10 shows that C_Min helps to extend the time to the first node failure. This is because C_Min avoids choosing the node which was chosen in the previous round, and therefore the sensor nodes are used more fairly. Similarly, the time to the first node failure extends when non-optimal scheduling schemes are applied.

Figures 11 and 12 study the performance of the scheduling schemes when the sensing duration varies. We assume that $E_c/E_m = 5$. It can be observed that the time until the first node failure and the network lifetime extend when the sensing duration increases. Similar to the previous results, C_Min outperforms the others.

6.2 Variable sensing range

Next, we evaluate the performance of the scheduling schemes under the scenario that the sensing ranges of the nodes are not identical. In our simulations, we restrict only the nodes that lie within 70 units from the centre of the object of interest to be the candidates of the node selection.

In Figs. 13 and 14, six scheduling schemes are compared:

(1) Minimum Cover (Min Cover)
(2) Minimum Sensing Range Cover (MSR)
(3) Conditional Minimum Sensing Range Cover (C_MSR)
(4) Hybrid Scheduling, MSR/Max–Min, $\gamma = 100$ (Hybrid)
(5) Minimum Battery Cost Cover (MBC)
(6) Maximum Minimum Residual Energy Cover (Max–Min)

Firstly, we study the performance of the scheduling schemes when E_r varies. MSR aims at finding a cover which preserves 360° coverage with minimum total energy consumption in sensing. It is expected that MSR and C_MSR will have a longer network lifetime than the others. However, Fig. 13 shows that Min Cover always has the longest network lifetime in the optimal case. This is because message overhead has crucial impact on the network lifetime. Although the total energy consumption in sensing in Min Cover may be more

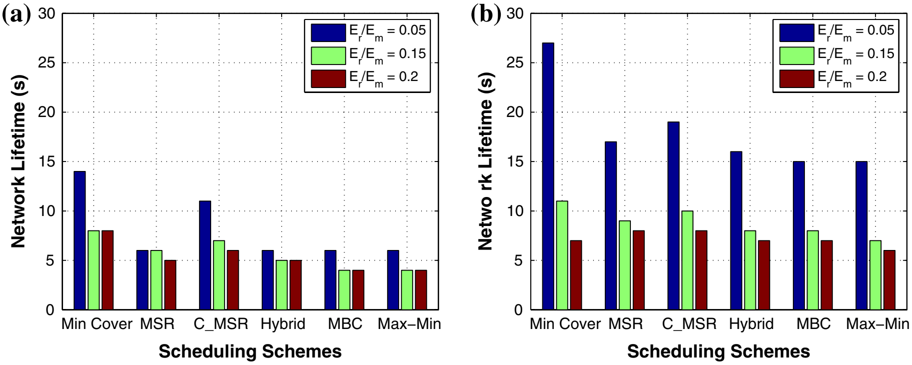

Fig. 13 Network lifetime comparison when E_r varies (variable sensing range). (**a**) Optimal. (**b**) Non-Optimal

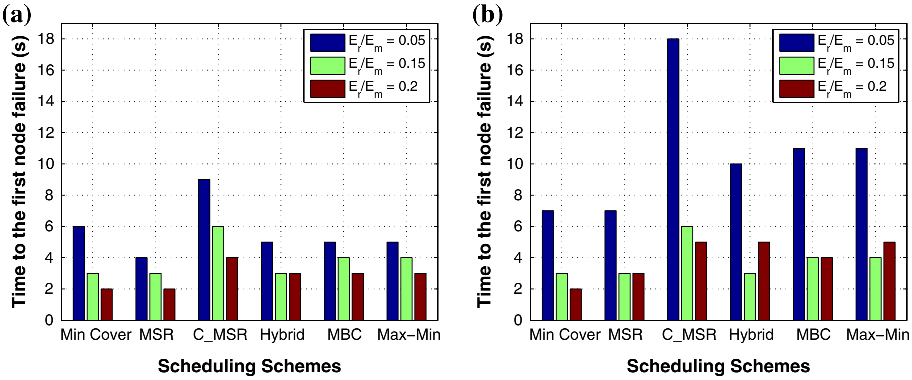

Fig. 14 First node failure comparison when E_r varies (variable sensing range). (**a**) Optimal. (**b**) Non-Optimal

than that of MSR or C_MSR, the message overhead of Min Cover is much less than the others.

In the non-optimal case, the message overhead of all the scheduling schemes becomes comparable, although Min Cover still consumes the least amount of energy in message communication. It should be noted that C_MSR and MSR have a longer lifetime than the others when $E_r/E_m = 0.2$. As E_r increases, the energy dissipated in sensing dominates the total energy consumption. It is advantageous to apply C_MSR or MSR when E_r is large. In addition, Fig. 14 shows that C_MSR helps to extend the time to the first node failure significantly. It is advantageous to apply non-optimal C_MSR when E_r is large. Figures 15 and 16 shows the result of the scheduling schemes when the sensing duration varies. We assume that $E_r/E_m = 0.05$. Similar to the previous results, non-optimal scheduling schemes have longer network lifetime. When sensing duration is 4 seconds, C_MSR and MSR perform better than Min Cover in terms of network lifetime in the non-optimal case. As shown in Fig. 16, C_MSR always has the longest time to the first node failure.

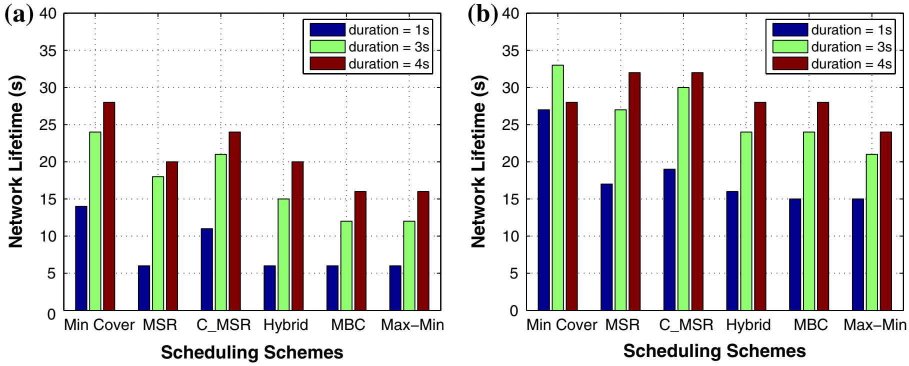

Fig. 15 Network lifetime comparison when duration varies (variable sensing range). (**a**) Optimal. (**b**) Non-Optimal

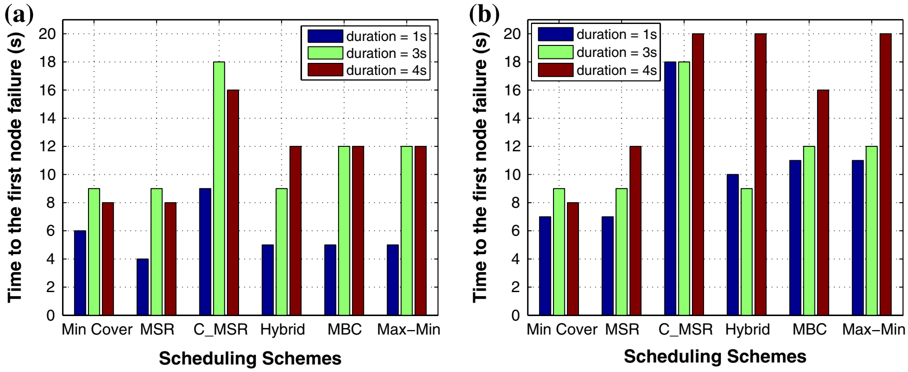

Fig. 16 First node failure comparison when duration varies (variable sensing range). (**a**) Optimal. (**b**) Non-Optimal

7 Conclusion

In this paper, we study the scheduling problem of monitoring the object of interest continuously with 360° coverage. We developed several scheduling schemes based on the Minimum Cover and Minimum Cost Cover algorithms. The simulation results show that our proposed Conditional Scheduling metric can help to improve the network lifetime as well as the time to the first node failure. If all the nodes possess identical sensing ranges, Conditional Minimum Cover should be applied. Otherwise, it would be advantageous to apply Conditional Minimum Sensing Range Cover algorithm.

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